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Cover image: Humpback whale mother-calf pair at Sainte Marie channel, Madagascar. © Cétamada association (Madagascar), 2017

Integrated approach to analyse benthic images from an autonomous underwater vehicle deployed at Pemba Island, Tanzania

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Abstract
Manual analysis of large amounts of benthic images is time consuming and costly. This challenge has led to the development of automated image analysis techniques such as CoralNet. The technique combines an online repository and machine learning to completely or partially automate classification of benthic images. Here, the integration of Coral Point Count with Excel Extensions (CPCe) and CoralNet is showcased. CPCe was applied to manually annotate images captured by an autonomous underwater vehicle (AUV) deployed at Pemba Island, Tanzania and then to train and build confidence in CoralNet to automatically annotate more images. Further, possible outputs that can be derived from assessing the relationships between the cover of benthic variables and depth are demonstrated.

Keywords: photo quadrat, benthic communities, annotation, depth effects

Introduction
Coral reefs are undergoing dramatic changes and shifts in their community structure, indicating the necessity to monitor these changes rapidly and on a large scale (Bryant *et al*., 2017). Until now, human observers have been the major source of information on coral reefs. This is limited to time and resources available for monitoring the reefs (Obura *et al*., 2019). The commonly used monitoring techniques for coral reefs include Length Intercept Transect (LIT), Point Intercept Transect (PIT), photo quadrat and video transect (Hill and Wilkinson, 2004). LIT and PIT both involve counting the number of times lifeforms are found along a transect. The photo quadrat captures digital images of substrates along the transect, whereas the video transect survey captures benthic communities as movies, allowing surveyors to collect sufficient data with minimal sampling effort and time (Leujak and Ormond, 2007). Random Point Count is applied on these photos and videos to estimate the percentage cover of benthic communities (Kohler and Gill, 2006). The photographic surveys are rapid to conduct, and are now widely adopted by coral reef monitoring programmes to determine benthic status and trends while also creating a permanent archive suitable for subsequent analysis (Williams *et al*., 2019). Collection of photos has also been improved by underwater vehicles (González-Rivero *et al*., 2016). However, it takes more time to annotate the photo or video quadrats (Molloy *et al*., 2013) because manual analysis of benthic images is time consuming and costly (Williams *et al*., 2019).

Coral Point Count with Excel Extensions (CPCe) is a software designed to improve the efficiency and convenience of performing the numerous image annotations. The tool works by randomly spreading a defined number of points over an underwater photo and then allowing the viewer to visually identify the benthos that lies underneath each point (Kohler and Gill, 2006). The annotation output may then be obtained from the programme, which includes both the point count and the benthic percentage cover from each individual photo quadrat, as well as the aggregated mean cover for all annotated photo quadrats. Although photos can be annotated with relative ease with CPCe, picture processing still requires manual

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processing by specialists who are able to identify the image features (Stokes and Deane, 2009). Additionally, varying human analytical accuracy may lead to bias (González-Rivero *et al*., 2016). Currently, benthic photo analysis has been simplified mainly to a collaboration between marine and computer scientists (Wilson *et al*., 2017).

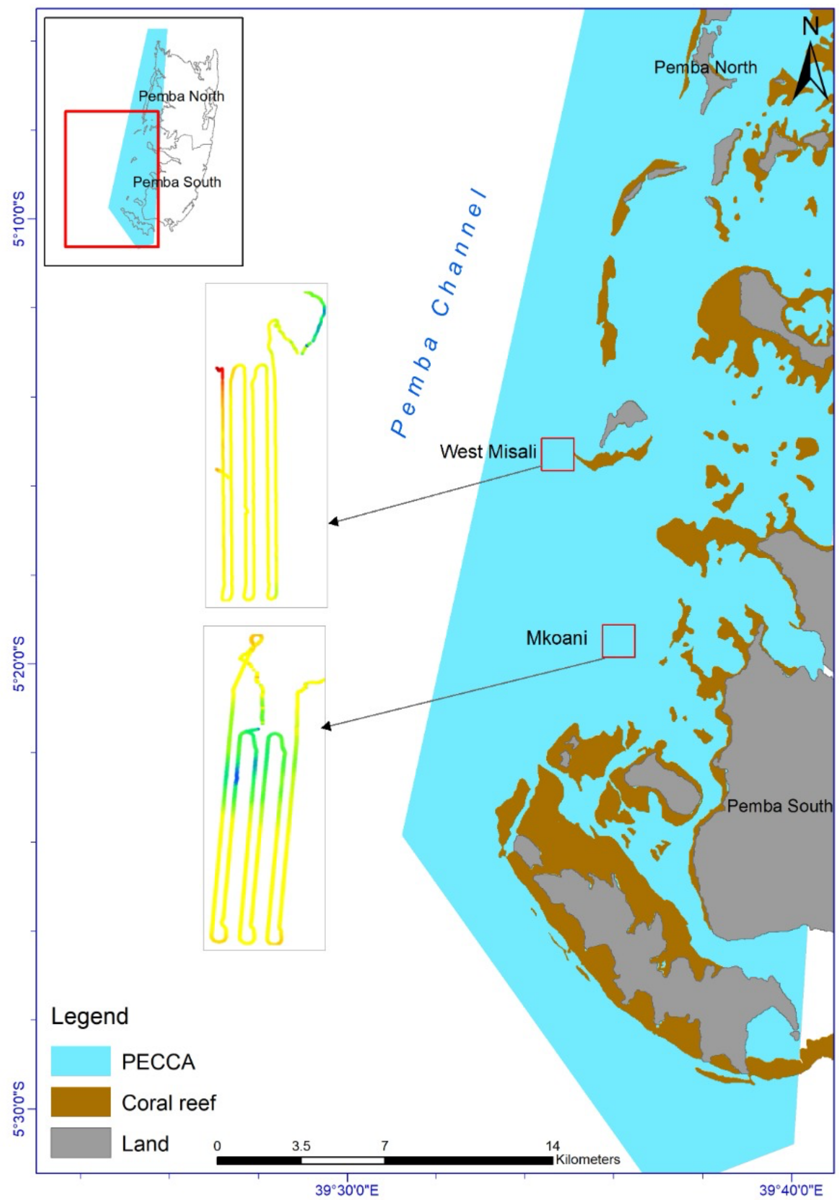

Figure 1. Map showing the sites of West Misali and Mkoani within the Pemba Channel Conservation Area (PECCA) in Tanzania and an inset of the track lines of autonomous underwater vehicle (AUV) deployed at each site. (Adapted from Osuka *et al*., 2021).

The challenge of accurately and rapidly analyzing large amounts of photos has led to the development of automated image analysis techniques (González-Rivero *et al*., 2016). CoralNet (https://coralnet.ucsd.edu/) is widely used, particularly for benthic image analysis. It combines an online repository, a tool for manually annotating photographs, and machine learning techniques to completely or partially automate classification of benthic photos (Beijbom *et al*., 2015; Williams *et al*., 2019). CoralNet's beta version has an accuracy comparable to human analysts of 80 % for corals and 48-66 % for algal groups such as macroalgae, turf algae, and coralline algae (Williams *et al*., 2019). On average, González-Rivero *et al.* (2016) discovered that machine annotation and approximation of benthic cover differed by 2.5 % from human annotators' estimates. In the other study by Williams *et al.*

(2019), they demonstrated how spatial and temporal changes in coral reef benthic cover may be accurately assessed using CoralNet through a completely automated image processing algorithm.

Oceanographic variables, either separately or in combination, can predict marine benthic composition with a high level of accuracy (Belanger *et al*., 2012). In benthic studies, depth has consistently been a powerful explanatory variable (Gray, 2001). It is the most important factor influencing marine benthic communities (Bergent *et al*., 2001). It is not a direct driver structuring benthic variables, but it frequently corresponds with predictions and gradients of a variety of dispersal variables particularly temperature, day length, and light penetration (McArthur *et al*., 2010). Olabarria (2006) revealed a correlation between depth and water quality parameters, as well as seafloor characteristics, which affect the settlement, recruiting, primary production and survival of benthic communities. This culminates in diverse benthic habitats and communities at various depths.

Habitat with high supply of resources and good conditions for survival are highly favoured by benthic communities. In particular, environments with a variety of resources, minimal tidal change, inaccessible or least interference by humans, are the most desirable habitats for the benthic organisms (Thrush *et al*., 1998). Since most photosynthesising biota are depth-limited, vertical water depth regulates the spatial distribution of benthic habitats (Wicaksono *et al*., 2019). Besides that, the type of substrate that supports the growth of the benthic community changes with depth. In the shallow and upper mesophotic depths, hard substrata are common, while sand predominates in the lower mesophotic depths (Osuka *et al*., 2021). In terms of benthic cover, hard coral cover has been found to peak at a depth of 10 m, while soft coral and turf algae peak at 20 m whereas the cover of crustose coraline algae (CCA) decreases with depth (Williams *et al*., 2013).

Here, CPCe is applied to manually annotate survey images captured by autonomous underwater vehicle (AUV) deployed at Pemba Island, Tanzania (Osuka *et al*., 2021), and then train and build confidence in CoralNet to automatically annotate more images. Further, the cover of benthic categories is derived from the annotation process and the relationships between the cover of benthic variables with depth is assessed.

Materials and methods

Study area

The shallow reefs of Pemba Island show a broad range of reef conditions, with some reefs in healthy states and dominated by hard coral cover, while others are in a degraded state with low coral cover (Grimsditch *et al*., 2009). An AUV was deployed in the Greater Pemba Channel at Misali, Mkoani and Tumbatu Shoals (see Osuka *et al*., 2021). This study utilised images collected by a low-flying AUV deployed at West Misali and Mkoani (Fig. 1).

Methods

Data were collected by the Teledyne Gavia Offshore Surveyor AUV in depths ranging from 10 and 45 m as described in Osuka *et al*. (2021). The AUV surveyed seafloor and water column properties and took seabed images using a Grasshopper, Sony ICX285 CCD sensor camera. The AUV was programmed to survey from 2 m above the seafloor for approximately 1-hour to capture detailed seabed photography. The control and command centre module of the AUV ensured that the vehicle followed a pre-designed track, collected high-resolution data including photos of the benthic community, and stored the data for later retrieval. The surveys were conducted from the RV *Angra Pequena*. Images of the 2 m-AUV mission had a length and width of ~1.7 m X ~1.3 m giving a footprint of 2.21 m^2. A total of 22 and 19 transects were created from AUV mission pathways in West Misali and Mkoani respectively. Each transect was 100 m in length within which 24 images were randomly selected and 25 points randomly assigned on each image (Table 1). A total of 984

Table 1. Sampling design for two sites showing the hierarchy from transect per site, number of images captured per transect and points selected per image.

Site	Transect (100 m)	Photos per transect (random)	Points per image (random)	Total points per site
West Misali	22	24	25	13,200
Mkoani	19	24	25	11,400

images (528 in West Misali and 456 in Mkoani) were selected for annotation.

Annotation process

The images were manually annotated with CPCe before being semi-automatically annotated in CoralNet (Fig. 2). The goal was to increase CoralNet's confidence in automating annotation of more images collected by the AUV. The annotation process was initially slow while using CPCe because an annotator had to identify the category of each of the 25 points overlaid on the image in the same way for each other image. Later, CPCe images and other raw photos were uploaded to CoralNet, increasing its confidence to around 60 %. The remaining photos were easily annotated using CoralNet, which provides autosuggestions of annotation points. Following the completion of the annotation process on CoralNet, the confidence

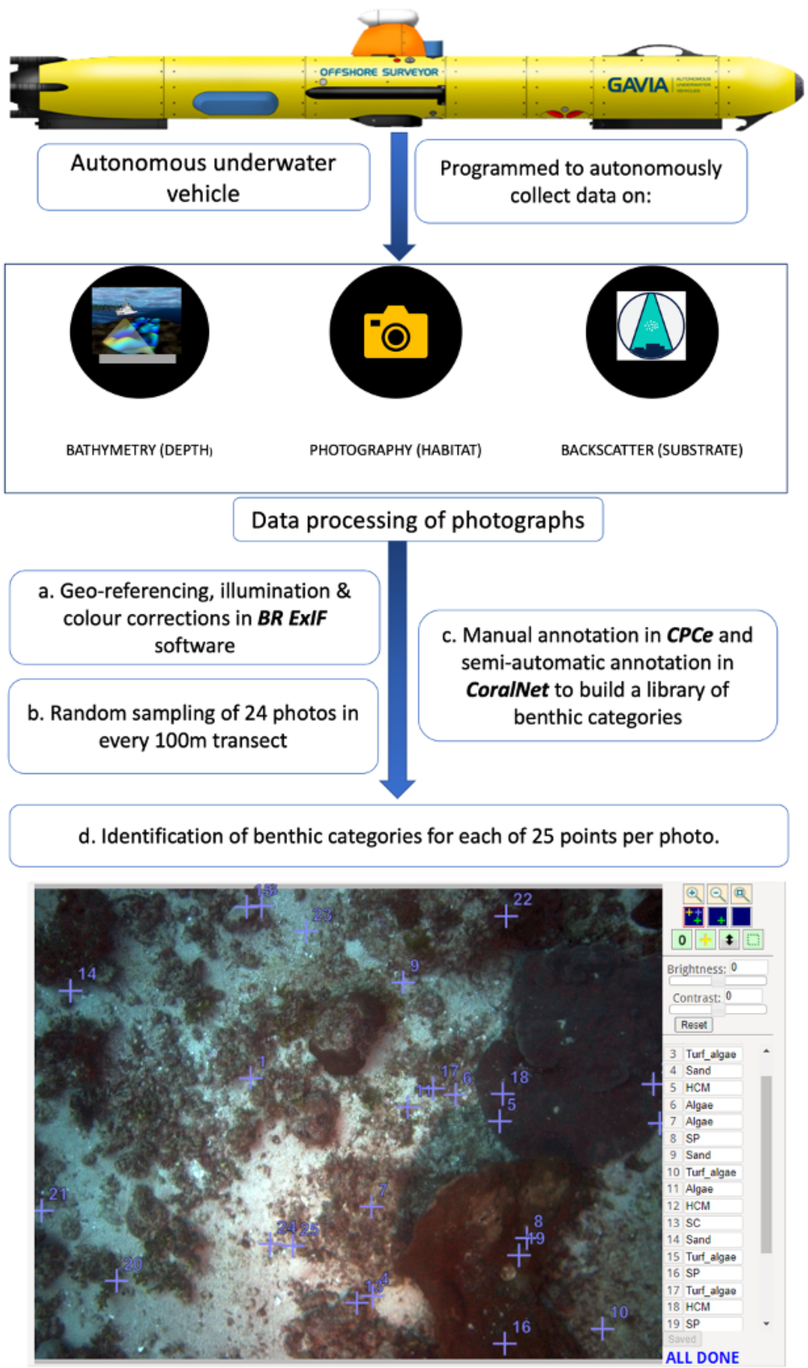

Figure 2. A graphic showing the autonomous underwater vehicle, data collected, data processing steps, and a sample of the photo with the benthic categories. HCM = hard coral massive, SC = soft coral, and SP = sponges.

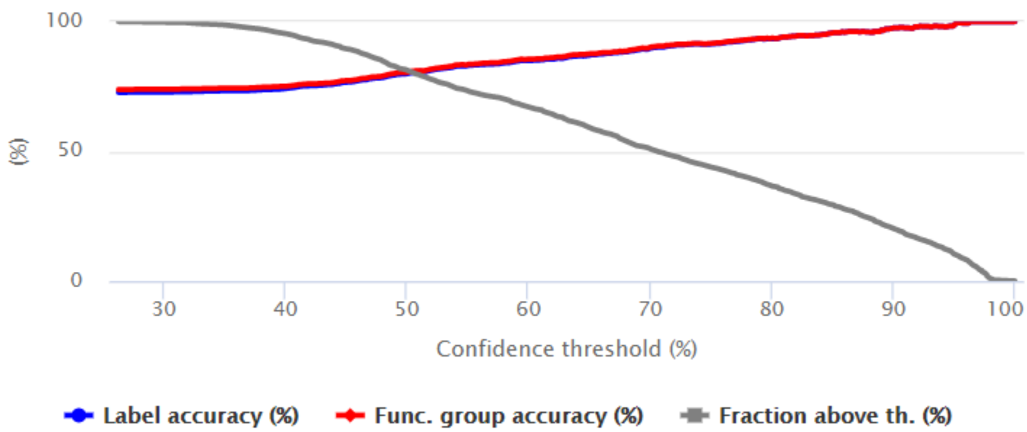

Figure 3. CoralNet computer vision backend showing sweeps of confidence thresholds (th.) for label and functional (func.) group accuracy and fraction above threshold.

threshold raised to 72.7 % (Fig. 3), with the goal of reaching at least 80 – 90 % for future automatic annotation and at least 50 % for within group accuracy. The final output from the CoralNet was uploaded and used for analysis in this study.

Analysis

The cover of benthic variables: hard coral, soft corals, crustose coralline algae (CCA), halimeda, sponge, turf algae, fleshy algae, invertebrates, rubble and sand determined from each photo, were summarised using

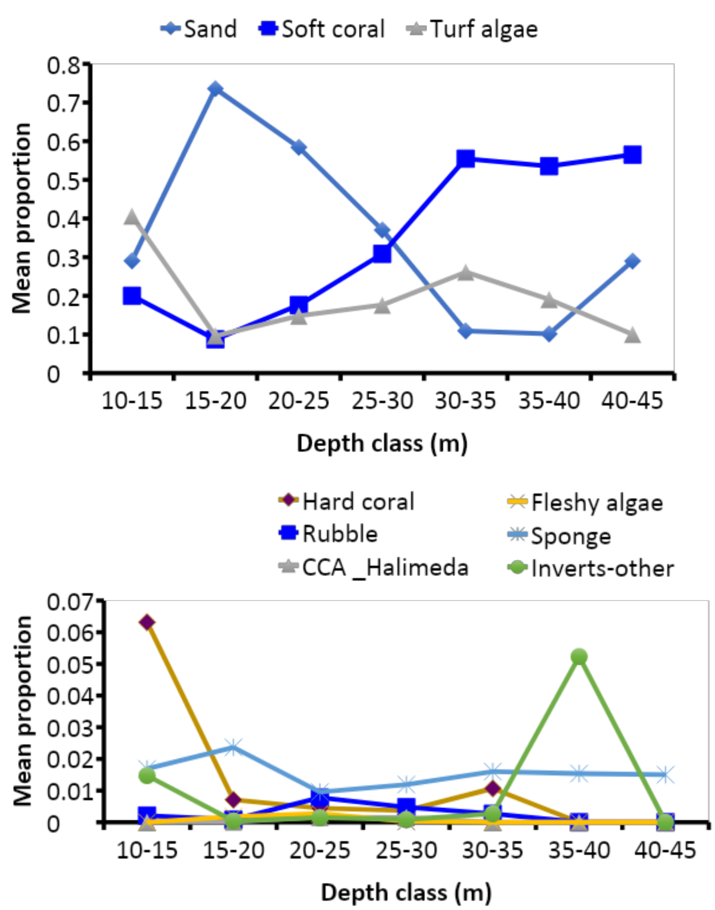

Figure 4. Mean proportion of nine benthic variables sampled from images captured by autonomous underwater vehicle.

means. Relationships between depth and cover of benthic variables were assessed using ordinary least squares regression.

Results

Sand, soft coral and turf algae were the most common benthic variables found in all depths with a mean cover of more than 1 % (Fig. 4). The cover of sand showed a peak of 75 % at 15-20 m depth class but decreased in the subsequent depth classes plateauing at 30-40 m before increasing again in 40-45 m water depth. Soft corals showed an upward trend reaching a maximum cover of about 55 % at 30-35 m and maintaining the cover all through to 45 m. The cover of turf algae was highest at 10-15 m but reduced to around 10 % at 15-20 m before increasing gradually in the subsequent depths up to 30-35 m. The cover then showed a downward trend reaching about 10 % at 40-45 m. Other variables notably hard coral, rubble, CCA-halimeda, fleshy algae, sponge and inverts-other showed low mean cover of <10 % in all depth classes (Fig. 4). Hard corals decreased in cover from about 6 % in 10-15 m to <1 % in depths >15 m. The cover of sponges oscillated between 1-2 % across all depth classes while invertebrates showed two peaks at 10-15 m and 35-40 m registering a cover of 1.5 % and 5 % respectively (Fig. 4).

Cover of certain benthic reef variables showed a significant relationship with depth (Table 2). Negative relationships with depth were evident in hard corals, sponges and sand while positive associations existed for soft corals and turf algae (Fig. 5). Every 10 m increase in the depth was associated with a 1.0 % and 33 % reduction in the cover of hard coral and sand respectively. On the contrary, soft corals and turf algae showed an increase of 24 % and 4.0 % for every 10 m increase in depth (Table 2). Other variables like sponges, rubble, fleshy algae and CCA did not show significant effects.

Discussion

The value of integrating tools to analyse images captured by AUVs is demonstrated. Despite several benefits of using CPCe to analyze photo-quadrats, it is a cumbersome, labour intensive process. However, integrating it with CoralNet helped improve the automation process. Indeed, several efforts globally have been undertaken to automate the benthic image processing and CoralNet is proving to be one possible option. Further research into its use and feasibility for the western Indian Ocean is still needed.

Hard coral and sand showed a significant decline with increasing depth, while soft coral and turf algae showed a different trend. High cover of benthic communities is expected in shallower than in deeper waters (Olabarria, 2006; Stefanoudis *et al*., 2019). Studies have shown benthic communities at 15–30 m are dominated by reef-building corals (Stefanoudis *et al*., 2019). Presence of sandy substrates is low in shallow depths where there is a high frequency of coral-algal interactions (Johns *et al*., 2018) but are expected to dominate in greater depths of >40 m (Osuka *et al*. 2021). While most benthic community classes decrease with depth, others such as turf algae can increase in coverage with depth (Stefanoudis *et al*., 2019). Dominance of turf algae in shallow reefs constitute an unstable phase that is moving towards a coral or macroalgae attractor (Mumby *et al*., 2007), with evidence suggesting a shift towards macroalgae dominance if herbivore density is low (Diaz-pulido and Mccook, 2002). Indeed, algae can survive in depths greater than 45 m (Nelson *et al*.,

Table 2. Regression coefficients of the relationship between depth and proportion of benthic variables from Pemba Island, Tanzania. Bolded p-values indicate significant relationships.

Variable	Slope	Error	Intercept	Error	r	p
Hard coral	-0.001	0.000	0.022	0.006	-0.091	**0.005**
Soft coral	0.024	0.002	-0.342	0.035	0.456	**0.001**
Sponge	-0.001	0.000	0.026	0.007	-0.061	0.059
Turf algae	0.004	0.002	0.052	0.037	0.088	**0.006**
Sand	-0.033	0.002	1.299	0.053	-0.421	**0.001**
Rubble	0.000	0.000	0.001	0.006	0.027	0.399
CCA _Halimeda	0.000	0.000	0.000	0.002	0.030	0.360
Fleshy algae	0.000	0.000	0.003	0.005	-0.010	0.748
Inverts-other	0.001	0.000	-0.009	0.003	0.139	**0.001**

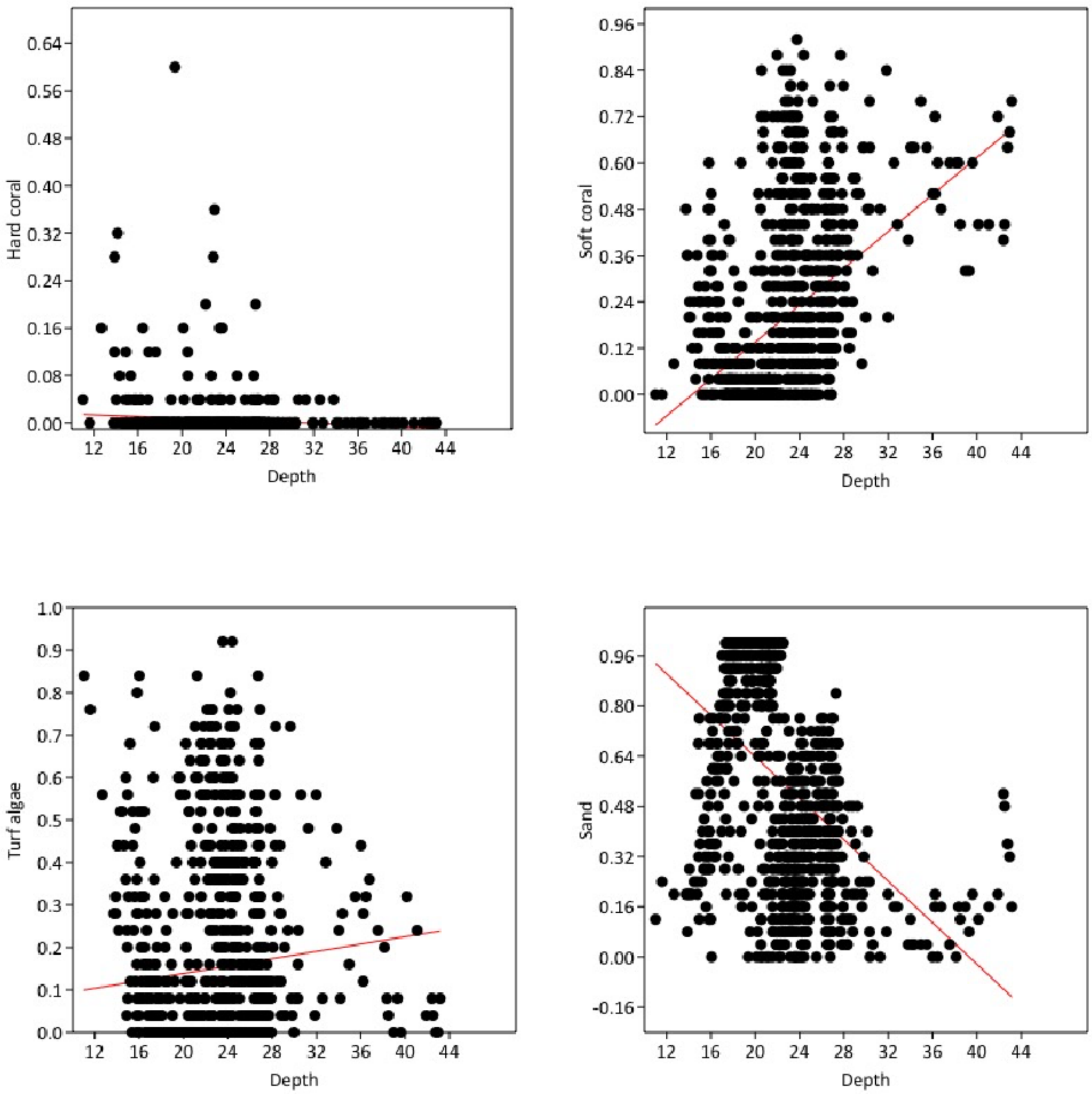

Figure 5. Linear relationships between depth and cover of benthic variables.

2015) and even in depths with 1 % of the surface irradiance, in contrast to seagrass and the majority of hard corals, which require more than 10 % of the surface irradiance to undergo photosynthesis (Wicaksono *et al*., 2019). On the other hand, soft coral supplement themselves by heterotrophy, which allows them to thrive in deeper waters (Williams *et al*., 2013). Because of variations in light attenuation underwater, benthic communities become restricted to particular depths (Duarte, 1991; Olabarria, 2006).

Image annotation is a time-consuming process, therefore finding a tool that will make the process easier becomes important, especially where a high number of images are collected by autonomous vehicles like the AUVs. CoralNet, Collaborative and Automated Tools for Analysis of Marine Imagery (CATAMI), SQUIDLE (https://squidle.org/about/) and BIIGLE (https://biigle.de/) are all web-based annotation tools that require consistent online connections to operate, but CPCe is a computer window-based tool that can be used offline but more importantly integrated with CoralNet to help improve the automation process, thereby reducing the amount of time used in analysing images. An alternative improvement would be the development of a computer-based annotation tool that could fully or semi automate the annotation process without requiring access to the internet.

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